Predictive Analytics to Improve Cancer Care Delivery: A Case Study in Serious Illness Communication

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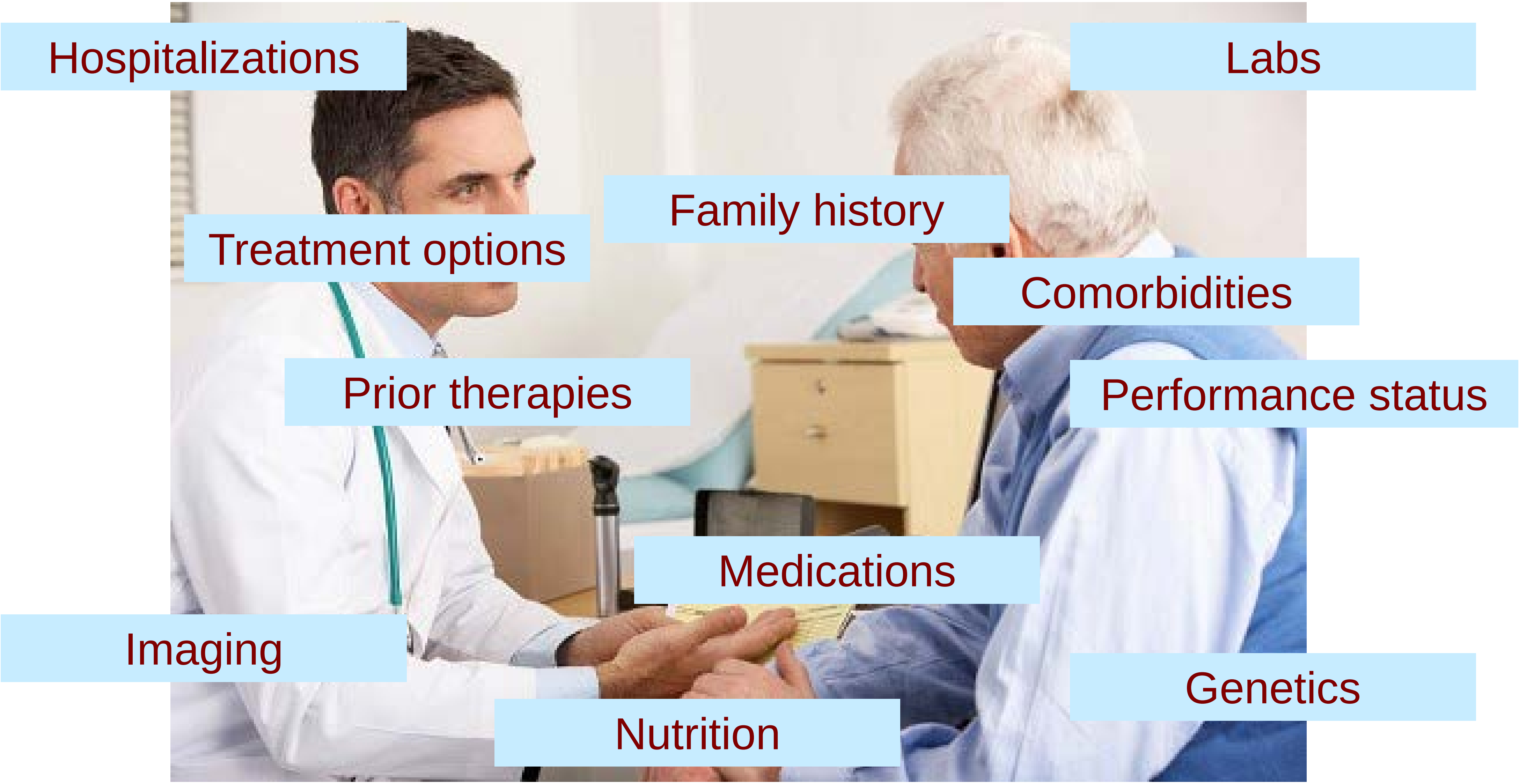
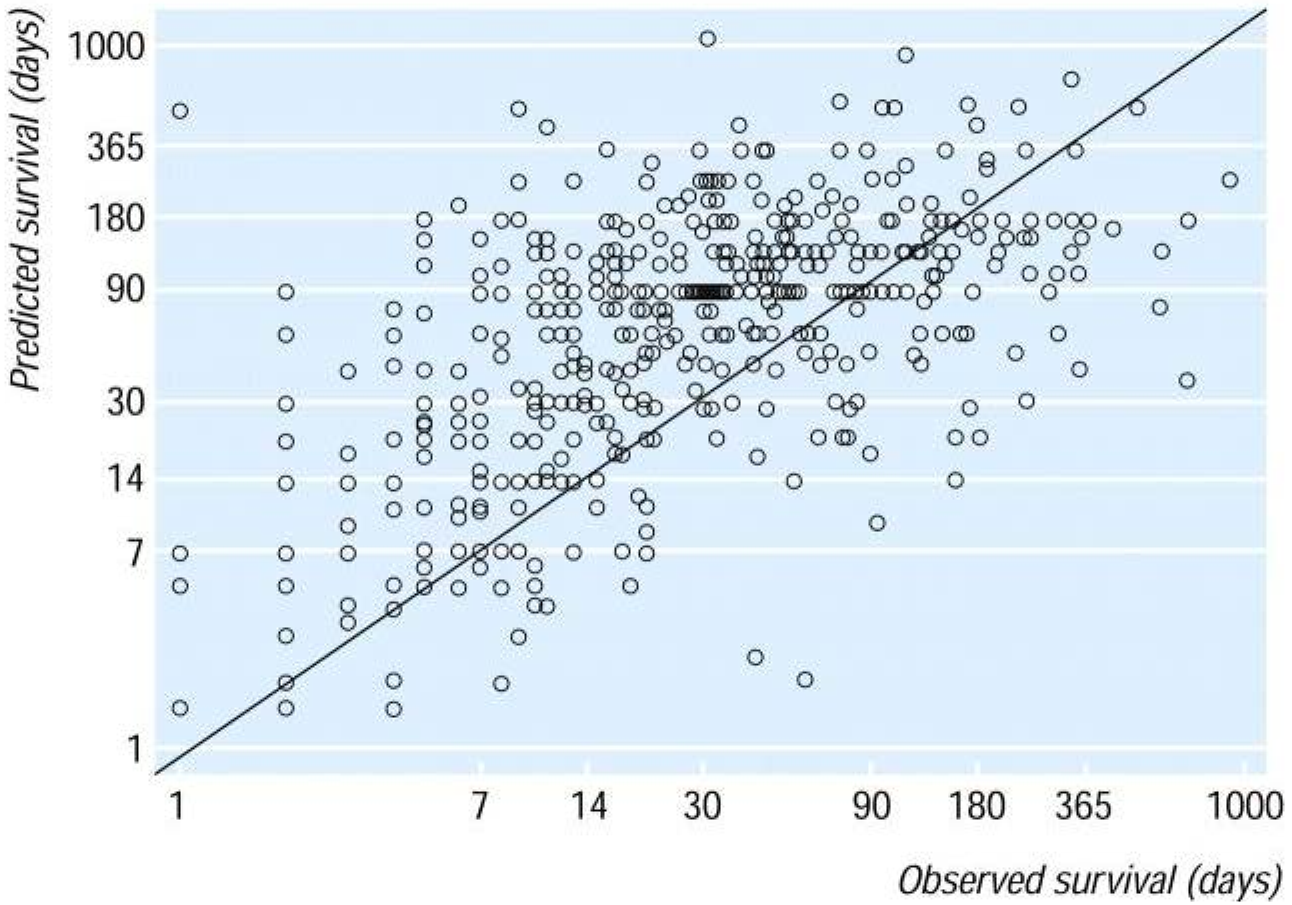
The Age of Big Data



How do you give a prognosis?

- Look at a randomized trial
- Look at population-level data
- Plug numbers into a model
- *Intuition*

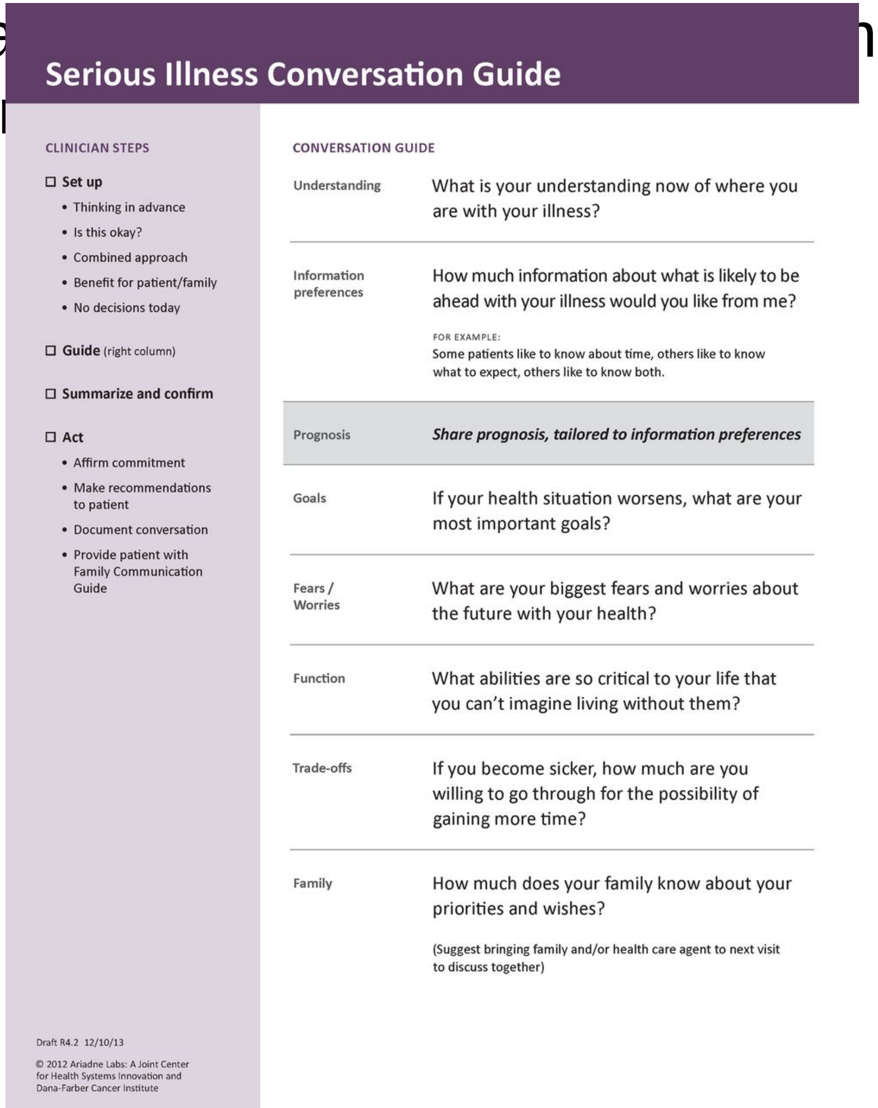


<u>Overly optimistic prognoses</u>

- Increase unwarranted utilization
- Delay conversations about goals of care, hospice

Our Experience: Serious Illness Conversations at Penn

- Early conversations a … mprove goal-concordant care, decrease unwa…



Serious Illness Conversation Guide

CLINICIAN STEPS

- ☐ **Set up**
  - Thinking in advance
  - Is this okay?
  - Combined approach
  - Benefit for patient/family
  - No decisions today
- ☐ **Guide** (right column)
- ☐ **Summarize and confirm**
- ☐ **Act**
  - Affirm commitment
  - Make recommendations to patient
  - Document conversation
  - Provide patient with Family Communication Guide

CONVERSATION GUIDE

Understanding	What is your understanding now of where you are with your illness?
Information preferences	How much information about what is likely to be ahead with your illness would you like from me? FOR EXAMPLE: Some patients like to know about time, others like to know what to expect, others like to know both.
Prognosis	*Share prognosis, tailored to information preferences*
Goals	If your health situation worsens, what are your most important goals?
Fears / Worries	What are your biggest fears and worries about the future with your health?
Function	What abilities are so critical to your life that you can't imagine living without them?
Trade-offs	If you become sicker, how much are you willing to go through for the possibility of gaining more time?
Family	How much does your family know about your priorities and wishes? (Suggest bringing family and/or health care agent to next visit to discuss together)

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Bernacki et al., JAMA Intern Med, 2019

Our Experience: Serious Illness Conversations at Penn

- Early conversations about goals and preferences improve goal-concordant care, decrease unwarranted end-of-life utilization
- Despite training, SIC documentation had been decreasing at Penn
- We developed a ML algorithm to predict palliative care need using structured EHR data

Variables	Examples	Features
Demographics	Age, Gender	
Comorbidities	33 Elixhauser comorbidities	• Total count • Recent*
EKG values*	QRS duration, BPM	• Total count • First/last value • Min/Max • Proportion ordered STAT
Laboratories*	CMP, CBC, LDH, Tumor markers, etc.	

- Missing observations imputed using mean or median imputation
- Feature selection: Drop highly correlated and zero variance variables

559 variables

Our approach

1. **Qualitative interviews to assess problem**
2. **Algorithm development and validation**
3. **Clinician surveys**
4. **Prospective validation**
5. **Feasibility pilot**
6. **Pragmatic randomized trial**

Moving from Retrospective to Prospective Validation

	AUC	[AUC CI]
Chester County Hospital	0.893	[0.86-0.92]
Pennsylvania Hospital	0.878	[0.84-0.91]
Breast	0.933	[0.89-0.96]
GI	0.817	[0.77-0.86]
Thoracic	0.801	[0.75-0.85]
Lymphoma	0.862	[0.79-0.92]
Myeloma	0.890	[0.83-0.94]
GU	0.875	[0.80-0.93]
Melanoma	0.814	[0.73-0.90]
Neuro	0.715	[0.61-0.82]
PPMC	0.812	[0.72-0.90]

Parikh et al, JAMA Network Open, 2019; Manz et al, ASCO, 2020

Pragmatic randomized trial: Intervention

Weekly SIC Email

- Comparative performance of providers over previous 4 weeks
- Link to list of high-risk patients

Review of high risk lists

- Review list of high risk patients for following week
- Option to opt out of automatic text message reminder

Automated text reminders

- Text reminder on morning of clinic

Our Outcome

Serious Illness Conversations	Control	Intervention	Adjusted Difference for Intervention Relative to Control, Percentage Points (95% CI)	P Value	Adjusted Difference for Intervention Relative to Control, Odds Ratio (95% CI)
All patient encounters	1.3% (155/12170)	4.6% (632/13889)	**3.3 (2.3-4.5)**	<.001	2.02 (1.44-2.83)
High-risk patient encounters	3.6% (77/2125)	15.2% (304/1999)	**11.6 (8.2-15.5)**	<.001	2.72 (1.73-4.28)

Conclusions and Lessons Learned

- Automated predictive analytics at the point of care can change clinician behavior, improve cancer care delivery, and potentially reduce unwarranted utilization
- Rigorous solicitation and incorporation of clinician views makes for a better algorithm
- *Prescriptive* analytics much more likely to improve care than *predictive* analytics
  - **The intervention is more important than the algorithm**
- We should treat analytics like we do drugs and diagnostics → subject to rigorous prospective trials

Thank you!

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